# Soil Moisture Modeling using Geostatistical Techniques at the O'Neal Ecological Reserve, Idaho

Jacob T. Tibbitts, Idaho State University, GIS Training and Research Center, 921 S. 8th Ave., Stop 8104, Pocatello, Idaho 83209-8104

**ABSTRACT**

Spatial interpolation techniques were used to model soil moisture patterns at the O'Neal Ecological Reserve in southeast Idaho and investigate interactive effects that may improve modeling results. The individual prediction models, created through ordinary kriging, were compared to a sequential Gaussian simulated prediction model(SGSIM). SGSIM always resulted in a lower magnitude of difference when compared to the ordinary kriging model. This may be due to the autocorrelation structure of each individual treatment which was more difficult to infer than for the entire dataset (in which SGSIM parameters were based upon). The degree of uncertainty in modeling the autocorrelation structure likely propagated through the prediction comparisons. SGSIM using 250 realizations proved most reliable in estimating the local soil moisture mean.

*KEYWORDS: rangelands, GIS, kriging, sequential Gaussian simulated prediction model*

## INTRODUCTION

Rangeland condition varies with numerous parameters including grazing management practices. Ellison (1954) noted the impact of grazing on vegetation and soil is primarily realized through "alterations of soil moisture." In more recent years, Gill (2007) examined difference in soil processes, namely water content, between grazing treatments compared to an area with 90 years of exclusion from grazing. Thomas and Squires (1991) argue that soil moisture is the principal determinant of productivity and is the primary indicator of rangeland condition.

To determine the effect of various grazing treatments on soil moisture, we developed a controlled experiment at the ISU O'Neal Ecological Reserve (Figure 1). The study site was divided into three pastures each with a different grazing treatment applied—total rest, rest-rotation grazing, and adaptive grazing (simulated holistic planned grazing [SHPG]). This paper describes the development of a soil moisture model that allows for evaluation of soil moisture within and between treatments.

## METHODS AND RESULTS

The data set used in this study consists of 145 stratified random sample points generated in ArcMap using the Hawth's Tools extension. The samples were stratified by pasture with an approximately equal number of sample points located in each treatment ($n$ = 49 in the total rest treatment; $n$ = 46 in rest-rotation grazing treatment; $n$ = 50 in the adaptive grazing treatment pastures). Throughout July 2006, four soil moisture measurements were taken and averaged at each sample point using Campbell Scientific, Inc. HydroSense (http://www.campbellsci. com/cs620) hand-held probe (10 cm) with accuracy of +/-3.0 % volumetric water content (electrical conductivity of <2 dS m-1). These data were then entered into a geodatabase within ArcGIS for further analysis.

SPOT 5 satellite imagery (10 x 10 m resolution) was acquired during July 2006, coincident with the field sampling campaign. This imagery was used to derive normalized difference vegetation indices (NDVI) to help corroborate and support soil moisture analysis as NDVI is typically negatively correlated with soil moisture (Adegoke and Carleton 2002). To do this, a cross-correlation between soil moisture and NDVI can be applied which may help bias our interpolation of soil moisture in unsampled areas assuming that the information contained in NDVI can reduce the variance of the soil moisture estimation error (Isaaks and Srivastava 1989). Cross-correlation may also be employed where soil moisture measurements were undersampled as compared to the exhaustively sampled NDVI (where each pixel has a value specific to that location). The processes involved in cross-correlation are further explained through cokriging, discussed below.

Spatial interpolation techniques were used to produce a soil moisture map of the O'Neal Ecological Reserve. There are various types of spatial interpolation and estimation used in this study. Kriging is a group of geostatistical techniques to interpolate the value of a variable $Z(x)$ (e.g. soil moisture $Z$ as a function of geographic location) at an unsampled location $x_o$ by using sampled measurements $z_i = Z(x_i)$, $i$=1, …, $n$ of the same variable at nearby locations $x_1, \ldots, x_n$ (Issaks and Srivastava 1989). The spatial dependence is quantified in terms of a variogram gamma$(x,y)$ and covariance function $c(x,y)$ of the variable. A variogram highlights the variance of a variable as a function of a specified geographic distance between measurements. This specified distance is called a lag. Kriging is known as a smoothing interpolator because real world differences between high value and low value areas become smooth,

possibly hiding "real" sudden changes. Ordinary kriging and cokriging were two kriging methods used in this study. Ordinary kriging is defined with the acronym BLUE for "best linear unbiased estimator." The term "best" is used because the algorithm minimizes the variance of the errors (Isaaks and Srivastava 1989); "linear" is used because kriging estimates are weighted linear combinations of the available data; and it is considered "unbiased" as the algorithm attempts to set $m_R$, (the mean residual or error) equal to 0. In comparision, cokriging is a spatial interpolation method that "minimizes the variance of the estimation error by exploiting cross-correlation between several variables" (Issaks and Srivastava 1989).

In addition to the above kriging methods, sequential Gaussian simulation was also used in this study. Sequential Gaussian simulation differs from kriging in that stochastic realizations are generated that honor global statistics as quantified by not only the variogram but also the histogram of the data. One can never expect kriging to reproduce the correct spatial association (global statistics) of the data in question (as measured by the variogram) because of the smoothing effect of kriging and for this reason sequential Gaussian simulation is sometimes preferred. However, to better ensure the correct geographical global statistics are applied, the user needs to define the joint probability model of properties at all grid locations taken together, not one-by-one as done in kriging. Sequential Gaussian simulation helps to overcome the smoothing effect of kriging and generates stochastic realizations that honor a specific geographic pattern as quantified by the variogram and histogram. Estimates are not only based on the variogram but also through the generation of a stochastic (random) sample from the joint probability distribution (Deutsch and Journel 1992).

The steps used to produce the model were as follows:

1. Ordinary kriging using the entire soil moisture dataset.
2. Co-kriging with NDVI.
3. Sequential Gaussian Simulation.

*Exploratory Data Analysis*

All data were statistically analyzed to determine distribution, relationship, and trend. Summary statistics of each grazing treatment are given in Table 1. To evaluate differences between mean percent soil moisture of each grazing treatment, we used a paired t-test. The results demonstrate differences in mean values between treatments in all cases (P = 0.05).

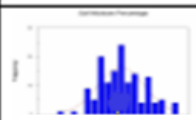
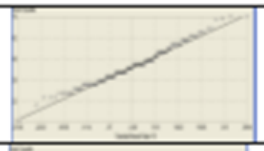
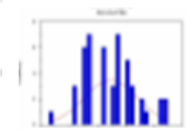
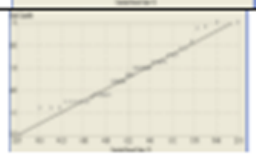
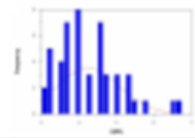
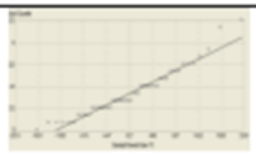
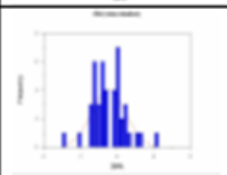
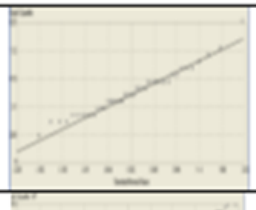
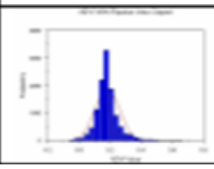
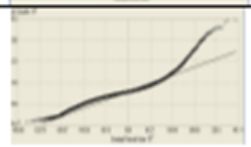
**Table 1. Volumetric water content (%) of soil in each individual treatment (samples taken in July, 2006).**

| | **Total Rest** | **Adaptive** | **Rest-Rotation** |
|---|---|---|---|
| **Mean** | 4.25 | 5.47 | 3.54 |
| **SD** | 0.8370 | 0.9396 | 0.9212 |
| **SEM** | 0.1196 | 0.1389 | 0.1356 |
| **n** | 49 | 44 | 48 |

*Note: The soil moisture dataset (n =141 points) had a mean percent volumetric water content of 4.44 with a standard deviation of 1.19.*

Each dataset was evaluated to describe its distribution and normality using the Kolmogorov-Smirnov Test (Table 2). The results indicate that each soil moisture dataset was normally distributed while the NDVI dataset was not normally distributed.

**Table 2. Normality summary of each dataset used in this project. Each soil moisture dataset was found to be normally distributed within a 95 % confidence interval. The NDVI dataset was not normally distributed within 95 % confidence.**

| | Histogram | Normal QQ Plot | K-S p-value | Ho: Dataset is normally distributed |
|---|---|---|---|---|
| SM% Entire Dataset |  |  | 0.1839 | Accept |
| SM% Adaptive (SHPG) |  |  | 0.3493 | Accept |
| SM% Total Rest |  |  | 0.2145 | Accept |
| SM% Rest-Rotation |  |  | 0.7029 | Accept |
| NDVI |  |  | 0.0000 | Reject |

*Note: SM% = soil moisture percent or percent volumetric water content.*

Next, trend was examined using the trend tool in ArcGIS 9.1 Geostatistical Analyst. Results suggest no strong regional trend within dataset. However, the trend tool was useful in noting that several of the highest soil moisture values were located in the adaptive grazing pasture.

The semivariogram cloud for the entire soil moisture dataset revealed that no single data point was responsible for the large squared differences observed. Also, a "transition zone" was identified and the majority of the large squared-differences (at the smaller lags) were found within the adaptive/SHPG grazing pasture (Figure 1).

The semivariogram cloud was analyzed by treatment, and the sample points with the largest squared differences at the smaller lag spacings were highlighted. These points were found nearest the boundary of each treatment and particularly near the adaptive pasture boundaries (Figure 2).

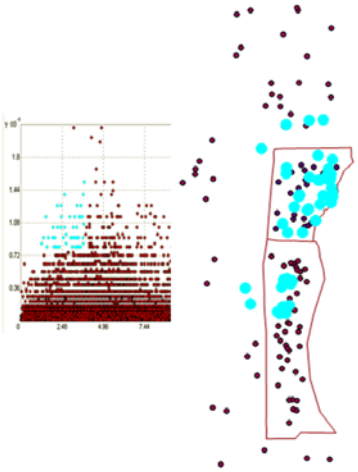


**Figure 1. Most of the large squared differences at the smaller lag spacings (transition zone) were linked to sample points in the simulated holistic planned grazing pasture (see the highlighted points in blue).**

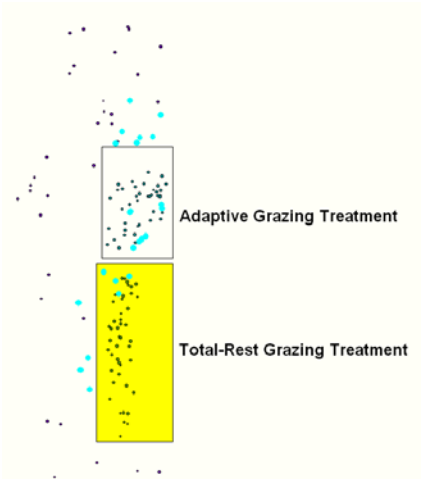



**Figure 2. Semivariogram clouds of each grazing treament were used to highlight the points with the largest squared differences in the transition zone. It is apparent that most of the difference occurs along the edges of each treatment near the fences.**

*Variography*

The sill is the semivariance value at which the variogram levels off. The sill is also used to refer to as the "amplitude" of a certain component of the semivariogram. Refrerring to figure 3, "sill" could refer to the overall sill (1.0) *or* to the difference (0.8) between the overall sill and the nugget (0.2); the interpretation depends upon the context. The range is the lag distance at which the semivariogram (or semivariogram component) reaches the sill value. Presumably, autocorrelation is effectively zero beyond the range. In variography, the definition of major and minor range is important in capturing spatial autocorrelation. In theory, the semivariogram value at the origin (0 lag) should be zero. If the semivariogram value is significantly different from zero at or near the origin, the semivariogram value is referred to as the "nugget". The nugget represents variability at distances smaller than the typical sample spacing; including measurement error (Isaaks and Srivastava 1989).

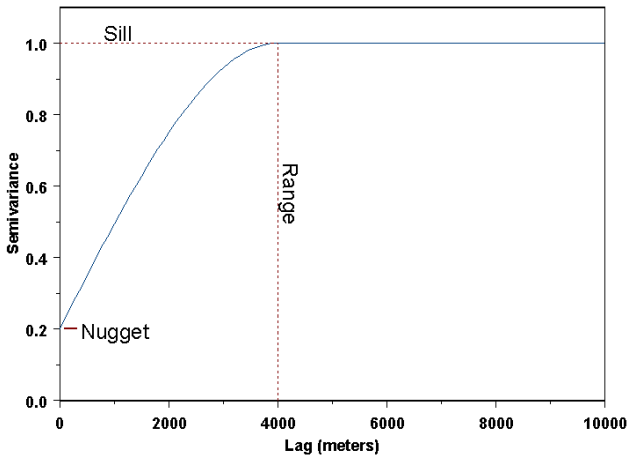



**Figure 3. Semivariogram showing the individual components of a semivariogram.**

Each of the components discussed above are important parts of variography. Variography was performed on the entire dataset as well as on each individual grazing treatment dataset. The autocorrelation structure of the entire dataset was fairly easy to infer, but each treatment, when separated, became more difficult to infer its autocorrelation structure. To accomplish this empirically, VarioWin software (http://www-sst.unil.ch/research/variowin/index.html) was used. The information produced within VarioWin was then applied in the ArcGIS Geostatistical Analyst.

To make sure that the "hump" (at a lag distance of ~560 meters; Figure 4) in the entire soil moisture dataset was not a trend that required "detrending", an omnidirectional semivariogram was produced in ArcGIS Geostatistical Analyst with 1st order trend removal to visualize the affect on the autocorrelation structure.

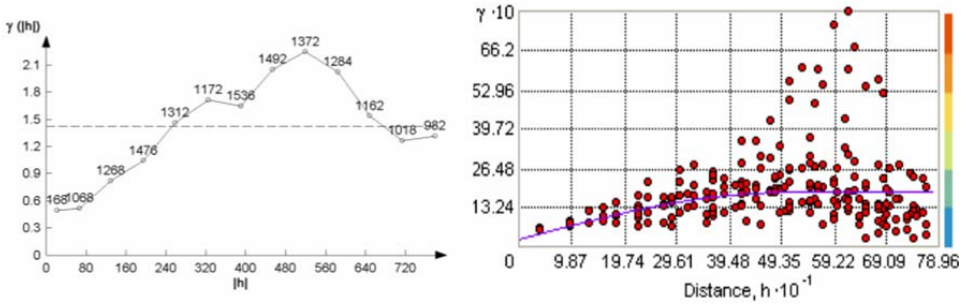



**Figure 4. This is an omnidirectional semivariogram of the entire soil moisture dataset. In all cases, variography was corroborated between Geostatistical Analyst and VarioWin.**

One requirement of kriging is that the data must not have regional/geographic trends which can skew interpolation estimates unfavorably. If trends are detected, detrending can be to prepare the data for subsequent kriging procedures. If the autocorrelation structures of an omnidirectional semivariogram change significantly with 1st order trend removal then there is a need for detrending. In this case, the difference was negligible and it was decided that the soil moisture variable did not require detrending.

In all cases, a nugget was applied and a nested model structure defined to better delineate the short-range spatial autocorrelation structure. Major and minor ranges were specified to better capture and represent spatial autocorrelation within and between model structures. The final model parameters, semivariogram, and covariance estimators for each soil moisture dataset are outlined below and in Figures 5-8.

*Variable- Soil Moisture (entire dataset)*
Lag Size: 65 Number of Lags: 12 Angular Tolerance: 30 Bandwidth: 3.0
Nugget: 0.05

Model 1- Manual Fit
Model Type: Exponential
Major Range: 50 Minor Range: 50 Direction: -
Partial Sill: 0.30

Model 2- Auto-Fit
Model Type: Spherical
Major Range: 770.5 Minor Range: 428 Direction: 63.6
Partial Sill: 1.46

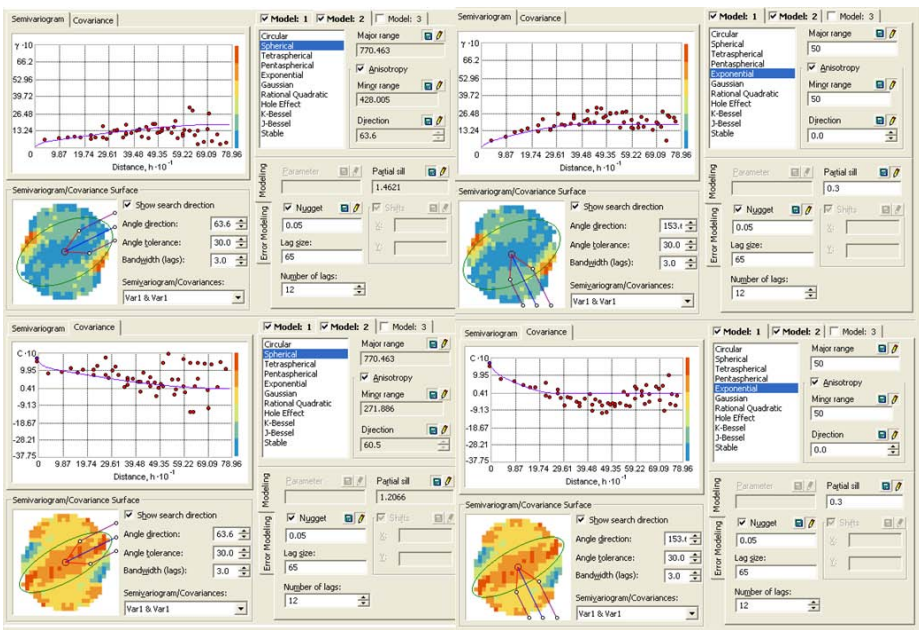


**Figure 5. Variography parameters, semivariogram estimators, and covariance estimators of the entire soil moisture dataset. Each estimator is displayed with major range (left column) and minor range (right column).**

*Variable- Soil Moisture (adaptive treatment [SHPG])*
Lag Size: 21 Number of Lags: 15 Angular Tolerance: 30 Bandwidth 3.0
Nugget: 0.20

Model 1- Manual Fit Model Type: Exponential Major Range: 50 Minor Range: 50
Direction:-

Partial Sill: 0.40

Model 2- Auto Fit Model Type: Spherical Major Range: 315 Minor Range: 212
Direction: 66
Partial Sill: 0.42

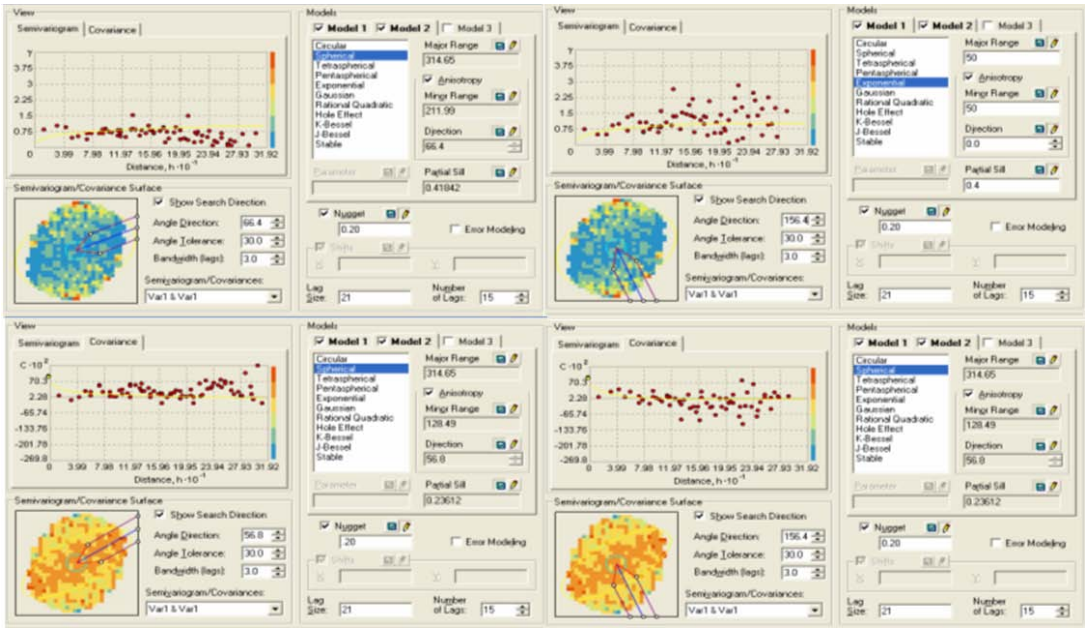


**Figure 6. Variography parameters, semivariogram estimators, and covariance estimators of the adaptive grazing treatment soil moisture dataset. Each estimator is displayed in terms of major range (left column) and minor range (right column).**

*Variable- Soil Moisture in Total Rest Treatment:*
Lag Size: 18 Number of Lags: 12 Angular Tolerance: 30 Bandwidth 3.0
Nugget: 0.05

Model 1- Manual Fit Model Type: Sperical Major Range: 50 Minor Range: 50
Direction:-
Partial Sill: 0.15

Model 2- Auto Fit Model Type: Spherical Major Range: 213 Minor Range: 197
Direction: 37
Partial Sill: 0.27

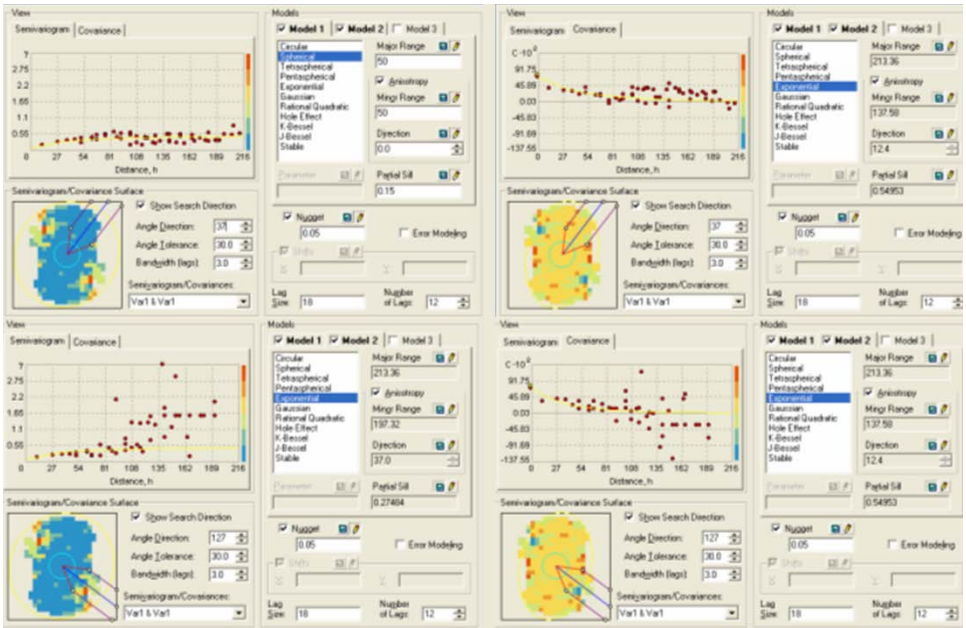


**Figure 7. Variography parameters, semivariogram estimators, and covariance estimators of the total rest grazing treatment soil moisture dataset. Each estimator is displayed in terms of major range (left column) and minor range (right column).**

*Variable- Soil Moisture in Rest Rotation Treatment:*
Lag Size: 85 Number of Lags: 15 Angular Tolerance: 30 Bandwidth 3.0
Nugget: 0.05

Model 1- Manual Fit Model Type: Exponential Major Range: 80 Minor Range: 80
Direction:-
Partial Sill: 0.35

Model 2- Auto Fit Model Type: Exponential Major Range: 1274 Minor Range: 634
Direction: 38
Partial Sill: 0.42

*Ordinary Kriging of Soil Moisture*

The models that best captured the soil moisture autocorrelation structure used short-range autocorrelation (nested transitive structure) with a small nugget (< 0.20). Both short-range and long-range variance anisotropy (the property of being directionally dependent, as opposed to isotropy, which means homogeneity of value expressed in all directions) was absent as determined by finding the quotient of the maximum range divided by the minimum range. Where anisotropy is present, the resulting value will be < 2.0 (Isaaks and Srivastava 1989). In addition, because no indication of pronounced geometric anisotropy was revealed in any of the models, a constrained circular search area was used for kriging (Isaaks and Srivastava 1989).

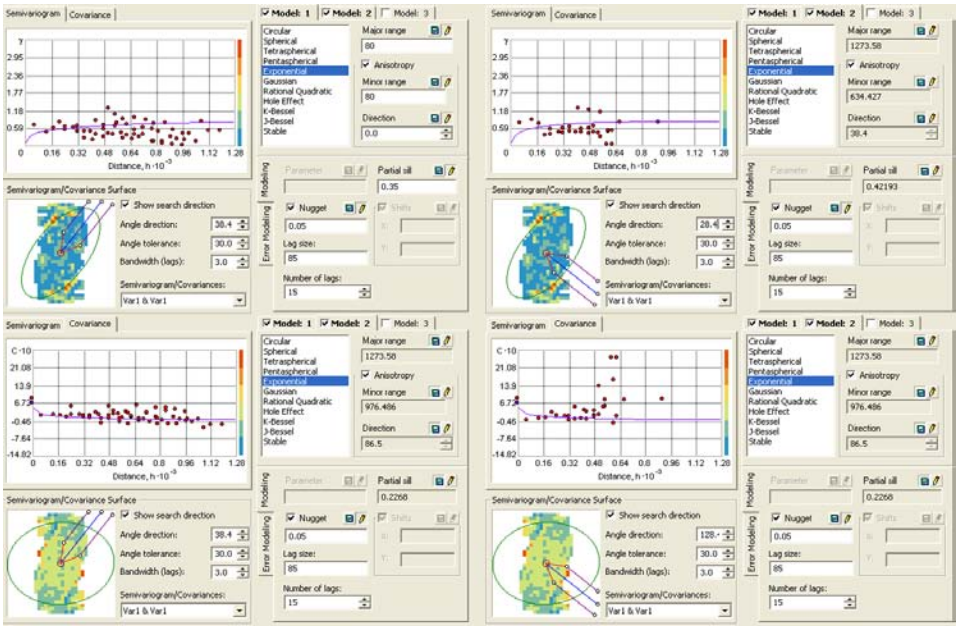


**Figure 8. Variography parameters, semivariogram estimators, and covariance estimators of the rest-rotation grazing treatment soil moisture dataset. Each estimator is displayed in terms of major range (left column) and minor range (right column).**

Since each of the variogram nuggets were small relative to the sill heights, a lower number of neighbors was specified in all cases because of the relative importance of the nugget compared to the sill (i.e., to help ensure that the closest neighboring samples were given the significant weight). The final kriging search strategies are summarized below and the prediction maps and standard error maps of each model are presented in Figures 9-12.

*Entire Soil Moisture Dataset Search Strategy:*

- Neighbors to Include: 15
  - Used 15 neighbors because the nugget is small relative to the sill and I want to ensure that the closest neighboring samples are given the significant weights.
- Include at Least: Not Checked
  - Do not want to "force" predictions where the data is lacking.
- Shape type: 4-Sectored (N-S)
  - Sampling regime consisted of measuring in same orientation
- Shape Major/Minor Semiaxes: 150/150
  - There was not pronounced geometric anisotropy so a circular search area of 150 is used.
  - Wanted a limited search that is constrained by the autocorrelation short-range variance component.

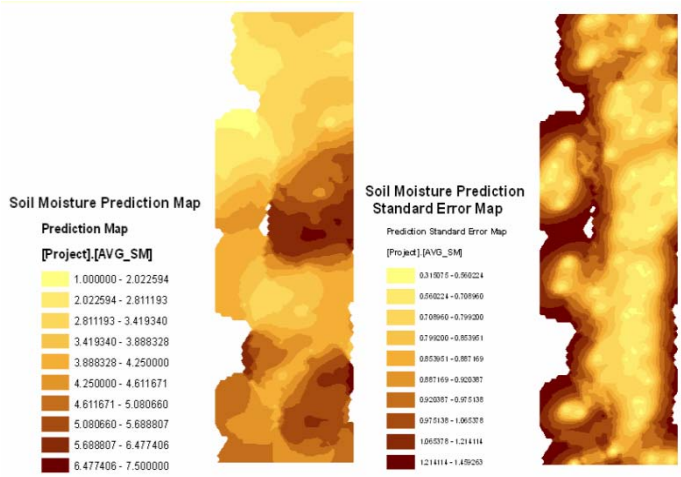



**Figure 9. Ordinary kriging prediction pap (left) and standard error map (right) of the entire soil moisture dataset.**

*Adaptive Grazing (SHPG) Treatment Search Strategy:*

- Neighbors to Include: 12
  - Used 12 neighbors because the nugget is small relative to the sill and I want to ensure that the closest neighboring samples are given the significant weights.
- Include at Least: Not Checked
  - Do not want to "force" predictions where the data is lacking.
- Shape type: 4-Sectored (N-S)
  - Sampling regime consisted of measuring in same orientation
- Shape Major/Minor Semiaxes: 100/100
  - There was not pronounced geometric anisotropy so a circular search area of 100 is used.
  - Wanted a limited search that is constrained by the autocorrelation short-range variance component.

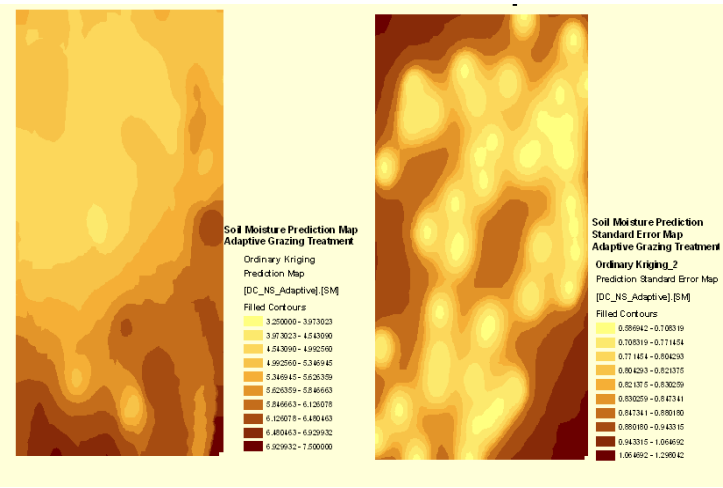



**Figure 10. Ordinary kriging prediction pap (left) and standard error map (right) of the adaptive grazing treatment soil moisture dataset.**

*Total Rest Grazing Treatment Search Strategy:*

- Neighbors to Include: 10
- Include at Least: Not Checked
  - Do not want to "force" predictions where the data is lacking.
- Shape type: 4-Sectored (N-S)
  - Sampling regime consisted of measuring in same orientation
- Shape Major/Minor Semiaxes: 100/100
  - There was not pronounced geometric anisotropy so a circular search area of 100 is used.
  - Wanted a limited search that is constrained by the autocorrelation short-range variance component.

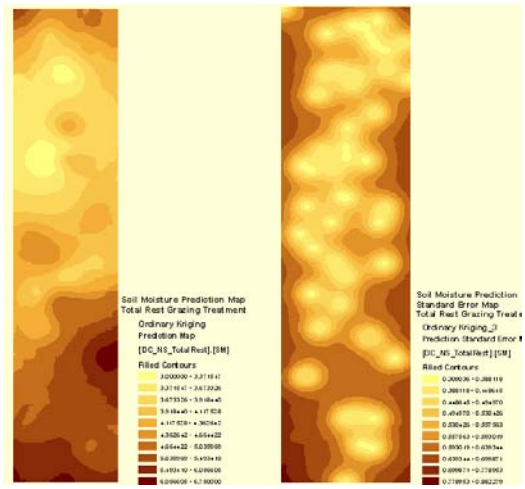



**Figure 11. Ordinary kriging prediction pap (left) and standard error map (right) of the total rest treatment soil moisture dataset.**

*Rest-Rotation Grazing Treatment Search Strategy:*

- Neighbors to Include: 16
- Include at Least: Not Checked
  - Do not want to "force" predictions where the data is lacking.
- Shape type: 4-Sectored (N-S)
  - Sampling regime consisted of measuring in same orientation
- Shape Major/Minor Semiaxes: 150/150
  - There was not pronounced geometric anisotropy so a circular search area of 150 is used.
  - Wanted a limited search that is constrained by the autocorrelation short-range variance component.

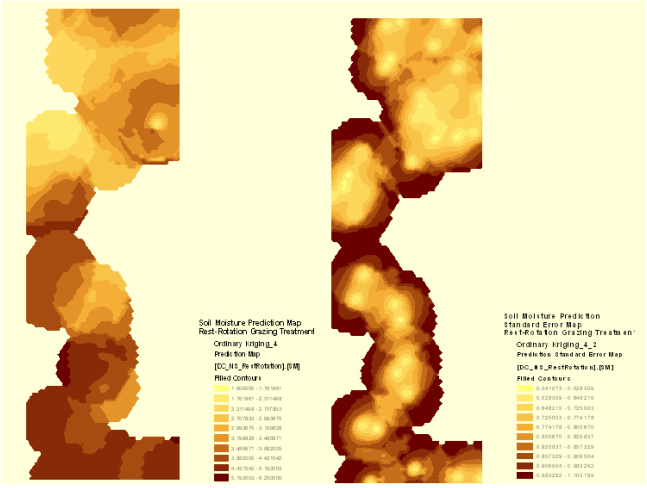



**Figure 12. Ordinary kriging prediction pap (left) and standard error map (right) of the rest-rotation grazing treatment soil moisture dataset.**

Cross validation statistics of each of the above models and their respective search strategies are given in Table 3. It should be noted that strict comparisons of these cross-validation statistics are not valid because although each treatment had a similar search strategy, each treatment area had its own unique autocorrelation model.

**Table 3. Ordinary kriging cross-validation statistics for each grazing treatment. Note how each statistics performance is evaluated in the far right column.**

| | Entire | Adaptive | Total Rest | Rest-Rotation | How error statistic is evaluated |
|---|---|---|---|---|---|
| **Mean Estimation Error** | -0.00793 | -0.02425 | -0.06875 | 0.02811 | Close to 0 |
| **Mean Standardized Error** | -0.003888 | -0.02248 | -0.07841 | 0.02477 | Close to 0 |
| **Root-Mean-Square Estimation Error** | 0.8259 | 0.8649 | 0.6095 | 1.007 | Small as possible |
| **Error Regression Slope** | 0.665 | 0.249 | 0.458 | 0.175 | Close to 1 |
| **Average Standard Error** | 0.7682 | 0.8264 | 0.5569 | 0.8201 | Small as possible |
| **Root-Mean-Square Standardized Error** | 1.134 | 1.079 | 1.007 | 1.306 | Close to 1 |
| **Ratio of Root-Mean-Square/Average Standard Error** | 1.075 | 1.047 | 1.094 | 1.228 | Close to 1 |

*Cokriging of Soil Moisture with NDVI*

The ability to improve the final soil moisture model by applying cokriging using NDVI was evaluated. Correlation between NDVI and each soil moisture dataset was determined using Pearson Correlation Coefficient (r). Results indicate that only the entire soil moisture dataset and the adaptive grazing soil moisture dataset bore any meaningful correlation with NDVI (p=0.05) (Table 4). Based upon this information, cokriging was performed for the entire soil moisture dataset and the adaptive grazing soil moisture dataset. However, it should be noted that although there were apparent significant correlations between these datasets, the fit to the regression line was poor.

**Table 4. Correlation statistics and hypothesis testing of the correlation between NDVI and soil moisture datasets.**

| | Pearson Correlation Coefficient (r) | tcrit | t | Ho: r=0 (95% CI) |
|---|---|---|---|---|
| **Entire Dataset** | -0.2045 | 1.979 | 2.4627 | Reject |
| **Adaptive** | -0.3360 | 2.0147 | 2.419 | Reject |
| **Total Rest** | -0.0340 | 2.0137 | 0.232 | Do not reject |
| **Rest Rotation** | -0.2395 | 2.0189 | 1.599 | Do not reject |

Variography was conducted using the NDVI dataset following the same protocols detailed above. The NDVI dataset autocorrelation structure was fairly easy to infer. This was expected given the amount of data available and the inherent spatial autocorrelation which exists within remotely sensed data. The final model parameters, semivariogram, and covariance estimators are summarized below and presented in Figure 13.

*Variable- NDVI Exhaustive Dataset:*
Lag Size: 35 Number of Lags: 16 Angular Tolerance: 30 Bandwidth: 3.0
Nugget: 0.0012

Model 1- Manual Fit
Model Type: Exponential
Major Range: 100 Minor Range: 100 Direction: -
Partial Sill: 0.0030

Model 2- Auto-Fit
Model Type: Spherical
Major Range: 558 Minor Range: 152 Direction: 9.2
Partial Sill: 0.0023

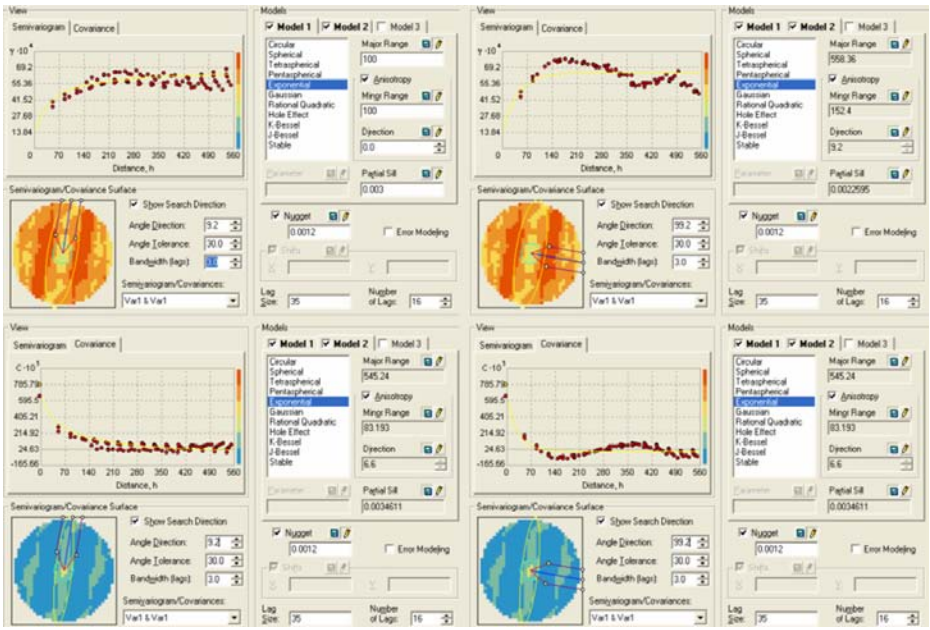


**Figure 13. Variography of NDVI exhaustive dataset.**

Cross-variography was performed on both the entire soil moisture dataset and the adaptive treatment dataset (with NDVI) using ArcGIS Geostatistical Analyst. Cross-variography is different from variography in that cross-variography is the process of modeling spatial autocorrelation of correlated variables (Issaks and Srivastava 1989). The best cross-covariance model parameters and cokriging strategy are summarized below.

*Cross-Variography Using Entire Soil Moisture Dataset (Primary Variable) and NDVI:*
Lag Size: 15 Number of Lags: 15 Angular Tolerance: 30 Bandwidth: 3.0

Cov(SM-SM)
Model 1 Model Type: Exponential
Major Range: 50 Minor Range: 50 Direction: -
Partial Sill: 2.30
Model 2 Model Type: Exponential
Major Range: 338 Minor Range: 139 Direction: 13
Partial Sill: 1.06 Nugget: 0

Cov(SM-NDVI)
Model 1 Model Type: Exponential
Major Range: 50 Minor Range: 50 Direction: -
Partial Sill: 0.0056
Model 2 Model Type: Exponential
Major Range: 338 Minor Range: 139 Direction: 13
Partial Sill: 0.0032 Nugget: 0

Cov(NDVI-NDVI)
Model 1 Model Type: Exponential
Major Range: 50 Minor Range: 50 Direction: -
Partial Sill: 0.1133
Model 2 Model Type: Exponential
Major Range: 338 Minor Range: 139 Direction: 13
Partial Sill: -0.0183

*Cokriging of Entire Dataset Search Strategy:*

- Neighbors to Include: 18
- Include at Least: Not Checked
  - Do not want to "force" predictions where the data is lacking.
- Shape type: 4-Sectored (N-S)
  - Sampling regime consisted of measuring in same orientation
- Shape Major/Minor Semiaxes: 150/150
  - There was not pronounced geometric anisotropy so a circular search area of 150 is used.
  - Wanted a limited search that is constrained by the autocorrelation short-range variance component.

Given that cokriging was evaluated as a way to improve soil moisture prediction, cross-validation statistics were compared between cokriging with NDVI and ordinary kriging. The results, shown in Table 5, indicate that from a strict comparison of cross-validation statistics, ordinary kriging performed better in all cases as compared to cokriging with NDVI.

**Table 5. Comparison of ordinary kriging of the entire soil moisture dataset and cokriging of the entire dataset with NDVI. The far-right column defines how each cross-validation statistic was evaluated. In all cases ordinary kriging performed better than cokriging (indicated by the *).**

| | Ordinary Kriging | Cokriging | How error statistic is evaluated |
|---|---|---|---|
| **Mean Estimation Error** | -0.00793 | 0.0164 | Close to 0 |
| **Mean Standardized Error** | -0.003888 | 0.01062 | Close to 0 |
| **Root-Mean-Square Estimation Error** | 0.8259 | 0.8977 | Small as possible |
| **Error Regression Slope** | 0.665 | 0.633 | Close to 1 |
| **Average Standard Error** | 0.7682 | 1.454 | Small as possible |
| **Root-Mean-Square Standardized Error** | 1.134 | 0.675 | Close to 1 |
| **Ratio of Root-Mean-Square/Average Standard Error** | 1.075 | 0.617 | Close to 1 |

Finding any cross-autocorrelation structure within the adaptive treatment dataset proved practically impossible. However, cokriging was still performed on the dataset and compared to ordinary kriging of the same adaptive grazing dataset. When the two predictive models were compared in ArcMap by calculating the difference between the ordinary kriging raster layer less the cokriging raster layer (using raster calculator), the magnitude of differences was determined to be unacceptable. The maximum difference was 1.71 which is ~32 % of the mean soil moisture value for the adaptive grazing pasture study area) (Figure 14).

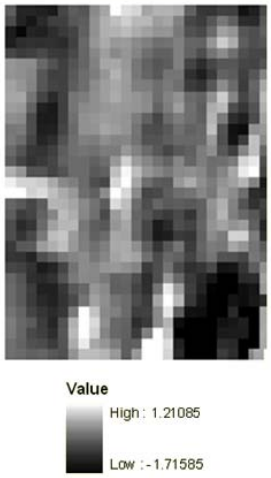



**Figure 16. Difference between the ordinary kriging-derived model and the cokriging-derived model (using NDVI) within the adaptive grazing (SHPG) treatment area. Notice the large magnitude of difference. The maximum difference is ~32 % of the mean soil moisture value of the adaptive treatment.**

*Sequential Gaussian Simulation of Soil Moisture (SGSIM)*

Sequential Gaussian simulation (SGSIM) was explored as a way to model soil moisture spatial variability using GSLIB Geostatistical Software Libray (http://www.gslib.com/). Since SGSIM requires data to exhibit multivariate Gaussian behavior (Deutsch and Journel 1992), this behavior was tested (Figure 15), with results indicating reasonable correspondence between at least 3 of the 4 indicator semivariograms (p=0.02, p=0.06, and p=0.08). The soil moisture dataset was considered to exhibit multivariate Gaussian behavior and SGSIM was used.

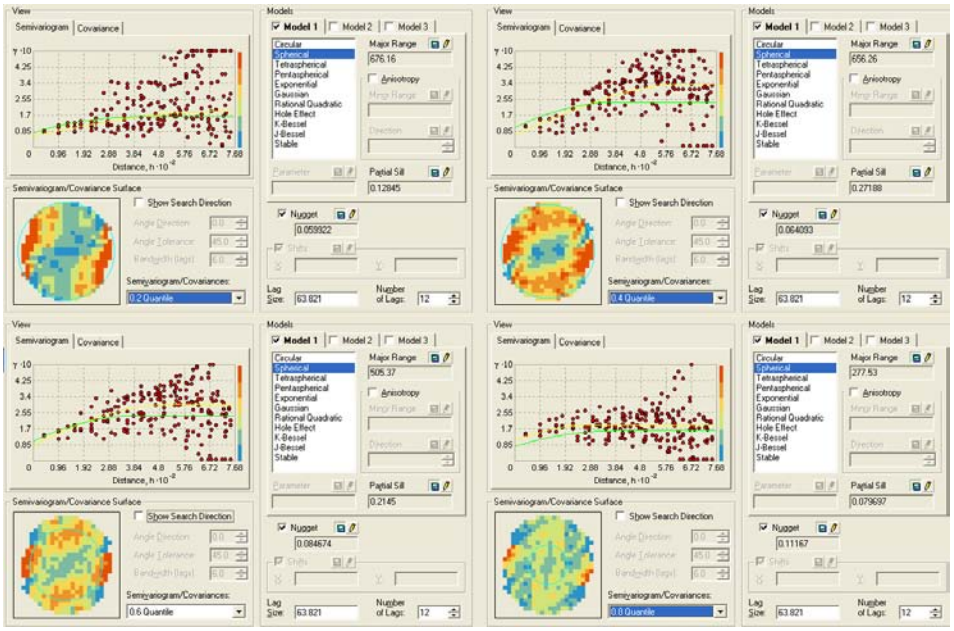


**Figure 15. Starting at the upper left image and continuing clockwise: p=0.02 threshold, p=0.04 threshold, p=0.06 threshold, and p=0.08 threshold. Notice the reasonable correspondence with the indicator semivariograms (green line).**

Since SGSIM requires variogram modeling in "normal-scored space" (Deutsch and Journel 1992), the best model to apply to the entire study area dataset (derived during variography processing above) was scaled to have a total sill of 1 and a low nugget near 0 (0.02). This scaling was corroborated in Geostatistical Analyst using the inputs below as model parameters (Figure 16).

**Normal Score Variogram Modeling of Entire Soil Moisture Dataset:**

Nugget 0.02

<u>Model No. 1-</u>
Type- Exponential
Partial sill- 0.17
Major range- 50
Minor range- 50

<u>Model No. 2-</u>
Type- Spherical
Partial sill- 0.81
Direction- 64
Major range- 771
Minor range- 428

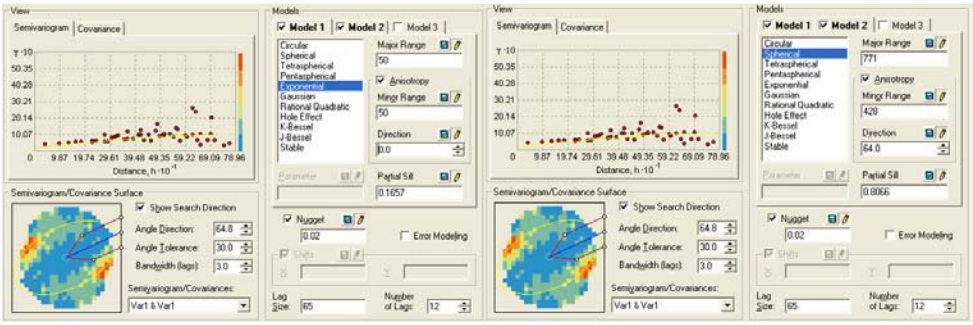


**Figure 16. Semivariogram of normal-scored soil moisture data. Left is the first nested transitive structure (Model 1) and right is the second nested transitive structure (Model 2). Notice how the parameter values match those used in SGSIM.**

It is typically desirable to know how many SGSIM realizations were required to reach a maximum difference, between realizations, of 5% of the soil moisture mean (Deutsch and Journel 1992). The soil moisture mean was ~4.5 and 5% of the mean was ~0.225%. Ten realizations were initially performed and the differences between the simulated maps were analyzed. The maximum difference (+/-) between the first and the tenth realization was 3.05 (note: a difference of <= 0.225 (<= 5 % of simulated mean soil moisture) was the target difference). Realizations were continued and the maximum magnitude of difference continued to decrease (Figure 17). A plot was constructed of these differences against the number of realizations to estimate the number of realizations needed (Figure 18). Based upon these data approximately 200-250 realizations were needed.

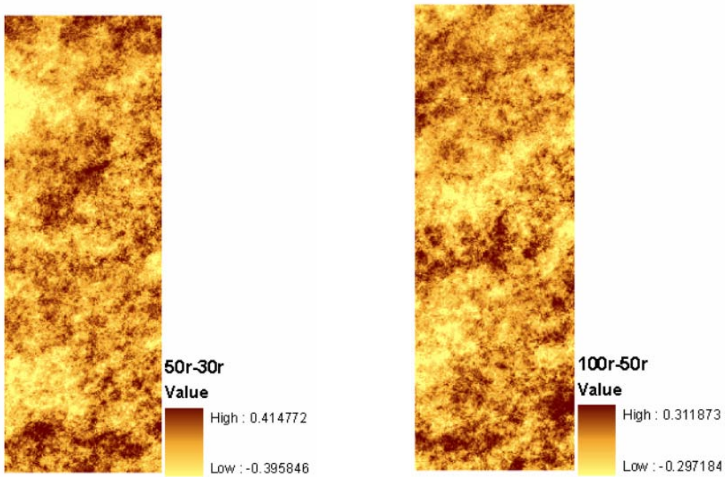



**Figure 17. Comparison maps showing the magnitude of difference between 50 and 30 realizations (left) and between 100 and 50 realizations (right). Notice how the magnitude of difference is decreasing with increasing simulation realizations.**

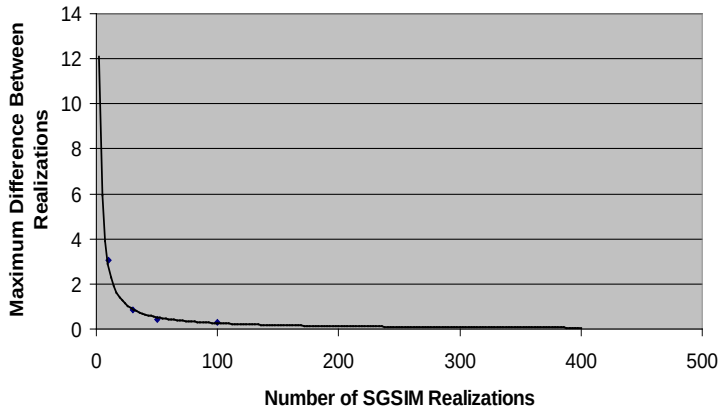



**Figure 18. Plot of realizations to the difference between realizations. There are 4 plotted points on the graph at 10, 30, 50, and 100 realizations. From this plot it was determined that 200-250 realizations were needed to return a difference of 0.225 or less.**

A total of 250 sequential Gaussian simulation realizations were performed which resulted in a difference of < 4 % of the soil moisture mean (i.e., within the target difference of +/- 5.0 %).

## SOIL MOISTURE MODEL COMPARISONS AND CONCLUSIONS

The individual prediction models, created through ordinary kriging, for each grazing treatment were compared to the sequential Gaussian simulated prediction model (Table 6). SGSIM always resulted in a lower magnitude of difference when compared to the ordinary kriging model. This may be due to the autocorrelation structure of each individual treatment which was more difficult to infer than for the entire dataset (in which SGSIM parameters were based upon). The degree of uncertainty in modeling the autocorrelation structure likely propagated through the prediction comparisons.

**Table 6. Comparison of SGSIM and the prediction model with the entire dataset (ordinary kriging) compared to each individually predicted map. The magnitude of difference that occurs with SGSIM is always smaller. Differences are expressed in volumetric water content (VWC) by percentage (%).**

| | SGSIM (250 Realizations) | Entire Dataset | SHPG Treatment | Total Rest Treatment | Rest-Rotation Treatment |
|---|---|---|---|---|---|
| **SGSIM (250 Realizations)** | N/A | 2.16074 | 1.755661 | 1.355103 | 2.17733 |
| **Ordinary Kriging** | 2.16074 | N/A | 2.86102 | 2.0484 | 2.82802 |

Analysis of the difference between the SGSIM soil moisture model (with 250 realizations) and the ordinary kriging prediction model was conducted. The comparison is shown in Figure 19.

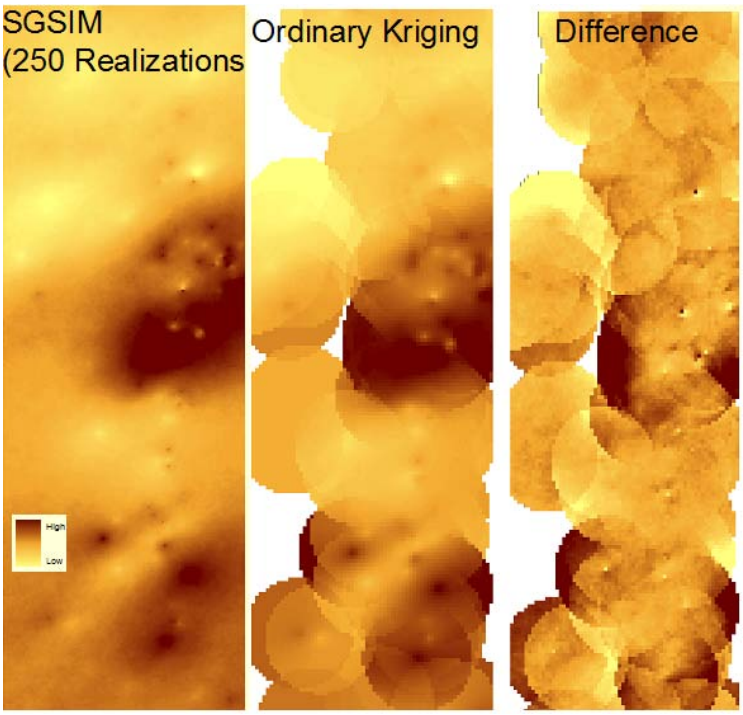



**Figure 19. Comparison of the SGSIM model with 250 realizations (left) to the ordinary kriging prediction model (center). The difference model shows a maximum difference of 2.16. Higher difference frequently falls in areas located near the borders (fences) between grazing treatments or areas of less dense sampling.**

The maximum difference between these models was 2.16. In all comparisons, the highest differences appear at the edges of data poor areas. Also, there were often high value differences near the borders of each grazing treatment. This degree of uncertainty was not necessarily acceptable, but understandable given the actual physical characteristics of fences and, as was previously shown, the mean soil moisture differences between treatments were significant. The highest squared differences of the semivariogram cloud were usually located near these same boundaries. In conclusion, the highest areas of uncertainty are in data poor areas and in geographic areas near or at grazing treatment transitions. For future sampling, it would be beneficial to measure more soil moisture values in these areas of concern. Overall, it is concluded that sequential Gaussian simulation with 250 realizations proved the most reliable in estimating the local soil moisture mean.

## ACKNOWLEDGEMENTS

This study was made possible by a grant from the National Aeronautics and Space Administration Goddard Space Flight Center (NNG06GD82G). ISU would also like to acknowledge the Idaho Delegation for their assistance in obtaining this grant.

## LITERATURE CITED

Adegoke, J.O., and A.M. Carleton, 2002. Relations Between Soil Moisture and Satellite Vegetation Indices in the U.S. Corn Belt. Journal of Hydrometeorology 3(3): 395-405

Deutsch, C.V., and A.G. Journel, 1992. GSLIB Geostatistical Software Library and User's Guide. Oxford University Press, New York

Ellison, L., 1954. Subalpine Vegetation of the Wasatch Plateau. Ecological Monographs. 24: 89–184

Gill, R.A., 2007. Influence of 90 Years of Protection from Grazing on Plant and Soil Processes in the Subalpine of the Wasatch Plateau, USA. Rangeland Ecology and Management 60(1): 88-98

Isaaks, E.H., and R. M Srivastava, 1989. An Introduction to Applied Geostatistics. Oxford University Press, New York

Thomas, D.A., and V.R. Squires, 1991. Available Soil Moisture as a Basis for Land Capability Assessment in Semiarid Regions. Plant Ecology 91(1-2): 183-189

**Recommended citation style:**

Tibbitts, J. 2010. Soil Moisture Modeling using Geostatistical Techniques at the O'Neal Ecological Reserve, Idaho. Pages 139-160 in K. T. Weber and K. Davis (Eds.), Final Report: Forecasting Rangeland Condition with GIS in Southeastern Idaho (NNG06GD82G). 189 pp.